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Optimizing lot sizing model for perishable bread products using genetic algorithm

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This research addresses order planning challenges related to perishable products, using bread products as a case study. The problem is how to efficiently manage the various bread products ordered by diverse customers, which requires distributors to determine the optimal number of products to order from suppliers. This study aims to formulate the problem as a lot-sizing model, considering various factors, including customer demand, inventory constraints, ordering capacity, return rate, and defect rate, to achieve a near or optimal solution. Therefore, determining the optimal order quantity to reduce the total ordering cost becomes a challenge in this study. However, most lot sizing problems are combinatorial and difficult to solve. Thus, this study uses the Genetic Algorithm (GA) as the main method to solve the lot sizing model and determine the optimal number of bread products to order. With GA, experiments have been conducted by combining the values of population, crossover, mutation, and generation parameters to maximize the feasibility value that represents the minimal total cost. The results obtained from the application of GA demonstrate its effectiveness in generating near or optimal solutions while also showing fast computational performance. By utilizing GA, distributors can effectively minimize wastage arising from expired or perishable products while simultaneously meeting customer demand more efficiently. As such, this research makes a significant contribution to the development of more effective and intelligent decision-making strategies in the domain of perishable products in bread distribution.

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1. INTRODUCTION

Order planning is an important operation management process involving strategic decision-making to optimize the ordering strategy while minimizing costs. It is an activity that manages ordering resources to achieve goals over a certain period, called a planning horizon. In the medium-term planning horizon, lot sizing is important because it decides the number of products distributed and where those products should take place to fulfil the demand while minimizing the production, setup/order, and inventory cost. In addition, most industries have multiple products that must be handled to make inventory management more complex [1], [2].

One of the interesting and challenging applications of the lot sizing problem is in the case of perishable products. It encompasses a range of products with limited shelf life and susceptibility to rapid spoilage or deterioration. This category comprises fresh food, dairy products, meat, poultry, fish, fruits, vegetables, bread goods, and pharmaceuticals. According to Tiseo [3], Indonesia is the world's fourth-largest country in household food waste, which makes this research urgent.

These products' quality and safety can be significantly impacted by their sensitivity to temperature, humidity, and other environmental conditions. Therefore, specialized handling, storage, and transportation protocols are essential to preserve their quality and prevent spoilage. Efficient management of perishable products is paramount for businesses striving for success, and accurate inventory tracking is pivotal in this endeavor. Managing perishable products is critical for companies that want to succeed, and inventory tracking becomes mission-critical.

For perishable products, efficient lot sizing management is crucial to optimize inventory and reduce wastage [4]. By using the right lot sizing model, companies can determine the optimal lot size for ordering or producing products, which can help match market demand and reduce the risk of damaged or expired products [5]. Lot sizing models also help find the right balance between ordering or production costs and inventory costs, which can help companies maximize their profits by avoiding unnecessary costs [6]. Additionally, the demand for perishable products often fluctuates, and lot sizing models can help companies efficiently plan orders or production to cope with this dynamic demand [7]. Perishable products require a quick response to market and demand changes, and lot sizing models can help companies plan orders better, ensuring the availability of the right stock at the right time [5].

Dynamic demand is another significant element that emerges in most practical applications. Determining inventory decisions is significantly more challenging, mainly when dealing with perishable products. Kırcı *et al.* [8] presented that it is crucial to determine the optimal replenishment strategy through demand prediction updates to reduce costs associated with overage and underage. Polotski *et al.* [9] proposed a production strategy that accounts for a finite product shelf-life and periodic demand changes. Dehghani, *et al.* [10] proposed a proactive transshipment policy to avoid future shortages and mitigate wastage under demand uncertainty for the blood supply chain using stochastic programming. Those costs also impact the pricing decisions for perishable products [11]–[13]. Feng *et al.* [14] developed an inventory model for perishable goods when the demand depends on the selling price, displayed stocks, and expiration date.

Complexity theory and computational experiments have demonstrated that the majority of lot-sizing problems pose significant challenges in terms of solvability. To address this complexity and attain near or optimal solutions within a reasonable computational timeframe, many researchers have turned to heuristic approaches for lot sizing problem-solving in recent years [15]–[17]. Among the various heuristic approaches, evolutionary computation, particularly Genetic Algorithms (GAs), has garnered considerable attention as the most prominent method. GA is based on an evolutionary algorithm that is inspired by the process of natural selection and natural genetics [9]. By mimicking those principles, genetic operators manipulate individuals in a population over some generations to increase their fitness.

Meta-heuristic approaches, especially using GA, have become one of the solutions in solving complex lot sizing problems. GAs can explore the solution space thoroughly, identify complex patterns, and find near or optimal solutions relatively quickly. This approach is particularly important because lot sizing often involves many products and complex production constraints. Other approaches, such as analytical and heuristic approaches, may not be able to provide accurate and efficient solutions in as short a time as GA [17].

Some notable examples of previous research have considered lot sizing problems and model solutions. Pasandideh *et al.* [18] proposed an optimized EOQ model using GA to address challenges in a two-tier supply chain system, such as backorder shortages, limited warehouse capacity, and order ceilings. However, the model does not consider perishable products and non-dynamic demand.

Azadeh *et al.* [19] proposed an inventory routing model with transshipment for perishable products using a GA-Taguchi-based approach. Although this model makes a valuable contribution, its weakness lies in focusing on only one product and the non-inclusion of ordering

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costs in its analysis. In the context of current research, it is important to consider multiple products and ordering costs to develop such models.

In addition, the model developed by Wang *et al*. [20] tackles the multilevel capacity lot-sizing problem and introduces improvements to fuzzy-GA. The results show that the proposed solution has better convergence and stability than the standard GA, producing an optimal lot size closer to the average optimal value. The difference between this research is its use in production, while the proposed research focuses more on ordering problems.

Kurade and Latpate [21] developed an EOQ model that considers demand variations in situations with no backlogging, partial back-logging, and full backlogging. They used a GA to optimize the economic order quantity under demand distribution assumptions such as log-normal or exponential distribution. A case study of a deteriorating product is used to illustrate the applicability of the proposed inventory model in a real-world context.

Panda *et al*. [22] addressed product damage control in an EOQ model, emphasizing reducing damage and storage costs through dynamic pre- and post-deterioration cumulative discount policies. The results show that this approach is more efficient than static pricing strategies in optimizing inventory. However, the model has significant drawbacks, namely using a static EOQ model that does not consider fluctuations in product demand over time and not using GA in its solution, which may limit its ability to deal with more complex or non-linear problems.

Based on the previous studies above, the lot sizing model cannot be solved analytically due to the complexity of the problem involving many interrelated variables and constraints. In lot sizing decisions, it is necessary to consider factors such as fluctuating customer demand, order cost, production cost, production capacity constraints, initial inventory, delivery time, perishable products, etc. These variables are often dynamic and influence each other, creating a complex solution search space. Employing analytical or heuristic methods to solve lot sizing models requires complicated mathematical formulas and sometimes cannot be solved explicitly. Therefore, analytical approaches often make it impossible to produce an optimal solution in a reasonable amount of time. In these cases, GA becomes a more realistic and efficient option, as it can explore complex solution spaces and find near or optimal solutions without requiring explicit analytical solutions that are difficult to generate.

This study is founded upon empirical research on perishable products, particularly bread distribution. In addition to addressing demand uncertainty, the investigation explores several challenges inherent to dealing with perishable items, including varying fixed shelf-life durations for different products, uncertain return rates, multi-period considerations, time-varying demand, and the intricacies of managing inventory and distribution from manufacturers to distributors and finally to customers. One notable impact of these challenges is the potential for a high return rate, which can significantly diminish the company's overall profitability.

This study presents a new approach for modelling lot size optimization focused on perishable products, contributing to enhancing inventory policy within a complex industrial environment. Moreover, it addresses relevant operational challenges that manufacturers and distributors commonly face, including return rate variability. This aspect of real-world systems has not yet undergone thorough investigation, rendering it a significant step towards developing interesting applications. The main objective of this research is to optimize order quantities for perishable products, considering multi-product, multi-customer, and multi-period environments.

The rest of the paper is organized as follows. In Section 2, we provide a formal definition of the problem and propose the integration of mathematical models and GA. Computational experiments and analysis are carried out in Section 3. Lastly, we provide conclusions and some future research directions in Section 4.

2. RESEARCH METHODS

2.1. Problem descriptions

This study investigates the intricacies of multi-product and multiple-period lot sizing problems concerning perishable commodities. Fig. 1 shows that the focal point of this investigation is the scenario involving a distributor's procurement of perishable goods, such as bread, from a manufacturer based on the retailers' demand. The present research establishes a designated product set denoted as p, with careful consideration given to the partitioning of the planning horizon into t discrete periods.

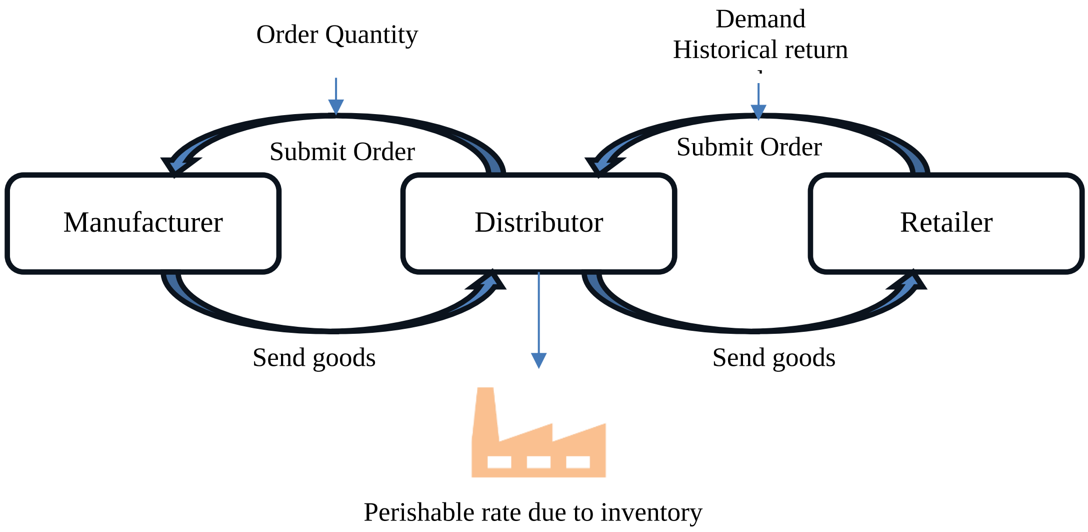

Fig. 1. An order planning system involves a single distributor ordering products from the manufacturer following the retailer's demand

The major problem in the real system is that there is no order planning from the distributor to the manufacturer. It impacts the inaccurate handling of stock items with limited shelf life, less than optimal utilization, and significant potential losses due to deterioration or expiration. The deterioration rate of this product causes a decrease in the quality of the product. The significant attribute of the quality of perishable products is their freshness. The freshness of the perishable product is usually tested by its appearance as examined by the consumers. When consumers decide between two similar perishable products with the same price, they will most likely choose the one that appears fresher. Therefore, it can be seen that deterioration is inversely proportional to its quality and consumer demand. This problem can significantly impact operational efficiency, costs, and customer satisfaction. Therefore, optimal order planning based on historical data is required to minimize overall costs.

Due to the model's NP-hardness and non-linearity, a model-based heuristic is proposed that focuses on solving small instances quickly, and a GA with a new progressive repair technique is created to handle large cases.

2.2. Notations and assumptions

The following notations are:

Index Set

- t : Number of periods, $t = 1, 2, 3, \dots, T$.
- p : Number of products, $p = 1, 2, 3, \dots, P$.
- f : One set of the total planning periods.

Parameter

- $A_{t,p}$: Ordering cost for product type p in period t (IDR).
- $H_{t,p}$: Holding cost for product type p in period t (IDR).
- $I_{t,p}$: The inventory level for product type p at the end of period t (units).
- $U_{t,p}$: Return cost for product type p in period t (IDR).
- $N_{t,p}$: Excess inventory cost for product type p in period t (IDR).
- $I_{t,p}^{v}$: Excess inventory level for product type p in period t (units).
- $E_{t,p}$: Estimated product return due to expiration for product type p in period t (units).
- $CI_{t,p}$: Perishable cost for inventory for product type p in period t (IDR).
- $D_{t,p}$: Demand for product type p in period t (units).
- K_{p} : Inventory level constraint for product type p (units).
- $Pr_{,t-f,p}$: Probability of the product being returned due to expiration at the last f days.
- G_{p} : The perishable rate during inventory (percentage).

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X_p : Deterioration rate of quality (percentage).

$O_{t,p}$: Original purchasing cost from manufacturer to distributor for product type p in period t (IDR).

J_p : Estimated duration to store products until they can be shipped to the next period (hours).

L_p : Estimated duration for the product to expire (days).

Independent Variable

$Q_{t,p}$: Order quantity for product type p in period t (units)

Dependent Variables (binary variables)

$s^v_{t,p}$: 1, if end inventory level exceeds the inventory level constraint for product type p in period t, 0, otherwise.

$Y_{t,p}$: 1, if there is a number of products ordered for product type p in period t, 0, otherwise.

$Z_{t,p}$: 1 if there are inventories for product type p at the end of period t, 0, otherwise.

TC : Total expected costs.

Due to the complexities of the model, the following assumptions are:

a. The demands for products are known and dynamic over the planning period.
b. Shortages are not allowed - demand must be fully satisfied.
c. There are no quantity discounts.
d. The processing costs for manufacturing the products are fixed over the planning period, except for return costs, which depend on a fluctuating return rate.
e. There are no transportation costs assumed for returning defective/unsold products

2.3. Mathematical model

The lot sizing problem for perishable products is formulated as a multi-period, multi-product model. This paper proposes an order planning methodology that considers the constraints imposed by post-delivery product degradation and storage degradation, as described in section 2.1. Therefore, perishability becomes essential in the distributor's decision to determine the optimal order. The total expected cost (TC) of the lot sizing model is derived from the ordering, inventory, excess inventory, return, and perishable costs due to inventory as formulated as follows:

$$\text{Min TC} = \sum_{t=1}^{T}\sum_{p=1}^{P}\big(A_{t,p}Y_{t,p} + H_{t,p}I_{t,p} + N_{t,p}I^v_{t,p}s^v_{t,p} + U_{t,p}E_{t,p} + I_{t,p}CI_{t,p}Z_{t,p}\big) \quad (1)$$

Subject to:

$$I_{t,p} = Q_{t,p} + I_{t-1,p} - D_{t,p} \qquad \forall_t \in T,\ \forall_p \in P. \quad (2)$$

$$I^v_{t,p} = I_{t,p} - K_p \qquad \forall_t \in T,\ \forall_p \in P \quad (3)$$

$$E_{t,p} = \frac{\sum_{t=1}^{T} D_{t,p}}{\sum_{t-f}^{T-f} Pr_{t-f,p}} D_{t,p} \qquad \forall_t \in T,\ \forall_p \in P \quad (4)$$

$$Z_{t,p} = \begin{cases} 1, \text{if } I_{t,p} > 0, \\ 0, \text{otherwise} \end{cases} \qquad \forall_t \in T,\ \forall_p \in P \quad (5)$$

$$CI_{t,p} = \left(100\% - G_p\right)O_{t,p} \qquad \forall_t \in T,\ \forall_p \in P \quad (6)$$

$$G_p = 100\% - \left(\frac{X_p J_p}{24}\right) \qquad \forall_p \in P \quad (7)$$

$$X_p = \frac{100\%}{L_p} \qquad \forall_p \in P \quad (8)$$

$$Y_{t,p} \in \{0,1\} \qquad \forall_t \in T,\ \forall_p \in P. \quad (9)$$

$$s^v_{t,p} = \begin{cases} 1, \text{if } I_{t,p} > K_p \\ 0, \text{otherwise} \end{cases} \qquad \forall_t \in T,\ \forall_p \in P. \quad (10)$$

$$Z_{t,p} \in \{0,1\} \qquad \forall_t \in T,\ \forall_p \in P. \quad (11)$$

$$Q_{t,p}, I_{t,p} \geq 0 \qquad \forall_t \in T,\ \forall_p \in P. \quad (12)$$

The objective function (1) minimizes the total expected cost of the ordering, inventory, excess inventory, return, and perishable costs due to inventory. Constraints (2) and (3) are, respectively, the inventory level and excess inventory level. To incorporate the deterioration, constraint (4) is the estimated product return due to expiration, while constraint (6) is the perishable cost for inventory. Then, constraint (7) is the imperishable rate during inventory, while constraint (8) imposes the deterioration rate of quality. In addition, constraint (5), (9), (10), and (11) define the binary variable, and constraint (12) ensures that the order quantity and the inventory level are non-negative.

Based on the constraints given in Eq. (7) and Eq. (8), perishability refers to the characteristics of products that deteriorate or degrade over time. In particular, it is influenced by two key factors: the rate of perishability during storage, which is denoted by Eq. (7), and the rate of quality deterioration, which is described by Eq. (8). Consequently, product storage has a considerable influence on the perishability rate. Furthermore, the rate at which the quality of the product deteriorates is also an important function related to the product's expiry date

2.4. Solution approach

Global optimization issues have been solved using metaheuristics in various engineering and scientific domains. Some algorithms are employed, such as particle swarm optimization [23], firefly algorithm [24], GA, etc. Due to its simple logic and precise search capabilities for pursuing global optimization, GA are a well-known and commonly utilized intelligent search method. This algorithm solves various optimization problems [16], [25]–[30], including lot sizing problems [20], [31]–[35], and transportation [36]. Lot sizing problems involve deciding how many products to order each period to minimize total inventory costs.

2.4.1. *Initial population*

This step concerns generating a chromosome randomly. The population (PoP) represents the various potential solutions of order quantity. The term "chromosome" refers to a fundamental concept borrowed from GA, representing a potential solution. Expressly, the chromosome in this study signifies a structured representation denoting the ordering quantity of product p during period t (Fig. 2).

$$\begin{bmatrix} Q_{1,1} & Q_{2,1} & \cdots & Q_{T,1} \\ \vdots & & \ddots & \vdots \\ Q_{1,P} & Q_{2,P} & \cdots & Q_{T,P} \end{bmatrix}$$

Fig. 2. The chromosome

2.4.2. *Evaluation*

A fitness value, which is the value of the objective function, must be assigned for a chromosome as soon as it is created when GA is used to solve an optimization problem. Some generated chromosomes, however, might not be practical due to limitations in the model provided by constraint (12). Even though there are several approaches in the literature (such as the penalty policy) to handle infeasible solutions Gen [22], this research has chosen to generate only feasible solutions due to the scale of the model in constraint (12). In other words, a chromosome that cannot be feasibly produced will be eliminated from the population. To do so, we develop a fitness function that incorporates a penalty policy to handle hard constraints (13) as formulated below:

$$s^s_{t,p} = \begin{cases} 1x10000000, \text{ if } I_{t,p} < 0 \\ 0, \qquad \text{otherwise} \end{cases} \tag{13}$$

where $s^s_{t,p}$ is the cost of the shortage inventory level determined based on the number of binaries at the time of the shortage in each period, which is then multiplied by the stepping value (10000000). Then, the fitness function (FF) is as follows

$$FF = \begin{cases} \dfrac{1}{\sum_{t=1}^{T}\sum_{p=1}^{P} s^s_{t,p}} 100, \text{ if } s^s_{t,p} > 0 \\ \dfrac{1}{TC} 1000 \qquad \text{if } s^s_{t,p} = 0 \end{cases} \tag{14}$$

The formula $\frac{1}{\sum_{t=1}^{T}\sum_{p=1}^{P} s^s_{t,p}} 100$, signifies the first step to eliminate the GA solution in the infeasible area. While formula $\frac{1}{TC}1000$ is used when the state of the infeasible area has been resolved so that the feasible GA solution starts at a higher fitness value. Thus, Eq. (14) aims to maximize the fitness value; the higher the fitness value, the lower the total costs.

2.4.3. *Crossover*

Chromosome pairs must be mated to produce children during a crossover phase, c. To do this, we randomly choose a pair of chromosomes with probability (Probability of crossover, P_c) from the Generation. One-point, two-point, multiple-point, and uniform crossover operators are just a few of the many varieties available. The one-point crossover operator used in this study operates as follows: Pick a random crossing point, split the parents at this location, and then exchange the tails to produce children. Fig. 3 presents graphical representations for the crossover operation for the order quantity vector with five periods in a product. A similar approach can be taken for another product vector.

Parents

$$[231 \quad 222 \quad 431 \quad \downarrow 156 \quad 124]$$
$$[125 \quad 595 \quad 214 \quad \downarrow 421 \quad 149]$$

Offspring

$$[231 \quad 222 \quad 431 \quad (421 \quad 149)]$$
$$[125 \quad 595 \quad 214 \quad (156 \quad 124)]$$

Fig. 3. An example of crossover operations

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2.4.4. *Mutation*

Some child chromosomes may undergo mutation to introduce variation in the population and prevent premature convergence to a sub-optimal solution. Mutation involves random changes (probability of mutation, P_m) to the genes in a chromosome (Fig. 4) for the mutation operators of order quantity. The mutation procedure of the algorithm uses the uniform operator [36], [37].

$$Q\ [231 \quad (222) \quad 431 \quad (156) \quad 124]$$
$$\downarrow$$
$$Q\ [231 \quad (156) \quad 431 \quad (222) \quad 124]$$

Fig. 4. An example of mutation operations

2.4.5. *Selection*

Chromosomes with higher fitness are more likely to be selected as the next Generation's parents. Selection methods such as elitist, roulette or tournament selection can be used to select the chromosomes to be inherited. Moreover, this research employed an elitist strategy.

2.4.6. *Stopping criteria*

The final step in a GA technique is to determine when the algorithm should terminate for an optimal solution. Properly defining stopping criteria is critical to avoid unnecessary computation and resources. We halt our study after 750 and 1000 generations (G_n). GA has the flexibility to handle complex optimization problems, including lot sizing problems. However, parameters of GA, such as population size, crossover probability, and mutation probability, must be carefully set to obtain satisfactory results.

3. RESULTS AND DISCUSSION

3.1 Experimental results

This section discusses important observations regarding order planning, total cost and decisions regarding orders in the context of a distributor purchasing perishable products (such as bread) over a given period of time, considering the return and perishability rates. In addition, a numerical example using real case data was used to examine the impact of return and perishability rates on a distributor's order planning over different time periods and products (Table 1 and Table 2).

In order to carry out an experimental analysis, the proposed lot-sizing model was modelled using Microsoft Excel integrated with a GA add-in, namely GeneHunter® software. All calculations were then performed on an Intel(R) Core(TM) i3-1115G4 processor at 3.0 GHz with up to 8 GB of RAM.

Table 1. Demand per each product

Demand per Product (D_p)	**Period (t)**						
	1	**2**	**3**	**4**	**5**	**6**	**7**
D_1	116	94	55	110	62	87	103
D_2	116	103	61	72	65	79	101
D_3	73	68	59	39	61	59	86
D_4	106	77	63	70	99	69	80

Table 2. Parameter values

Parameter	**Product**			
	1	**2**	**3**	**4**
$A_{t,p}$	75000	50000	60000	80000
$H_{t,p}$	1500	500	1000	1750
$U_{t,p}$	10800	3600	10500	9000
$N_{t,p}$	1500	500	1000	1750
K_p	10	15	10	10
J_p	16	16	16	16
L_p	8	8	8	6

This investigation considers one distributor ordering various bread products from the supplier. The proposed model, formulated in this study, is then applied to an actual business scenario involving a bread company in Yogyakarta. Relevant parameters were derived using historical data, and the mathematical model was developed and implemented using a spreadsheet. Given the complexity of the model, GA was used for optimization purposes.

This research presents an innovative experimental approach to designing lot sizing planning strategies using GA. GA is adopted as a powerful optimization tool capable of handling the complex challenge of determining the most optimal lot size in a supply chain context. To analyze and optimize the performance of order planning, we have explored a wide range of GA parameters, forming 12 combinations of GA parameter values (Table 3 and Table 4). The parameter values include population with values of 80, 90, 100, 125, 140, and 150, crossover with values of 0.65, 0.75, 0.80, 0.90, and 0.85, and mutation with values of 0.02, 0.05, 0.01, 0.03, 0.04, and 0.025. In addition, we also consider generations with values of 750 and 1000 as key factors in measuring efficiency.

This experiment is particularly important as it refers to the importance of optimal GA parameter settings in achieving the most accurate and efficient solution. By conducting various tests and analyses on combinations of these parameters, this research provides an in-depth understanding of how GA parameters can affect the outcome of lot size planning. In addition, involving the computational time factor in this research ensures that the resulting solution is also practical in its application.

Based on the results in Table 3 and Table 4, one of the key aspects of the GA capabilities in this study is its ability to optimize the fitness function to maximize the desired value. In the context of lot sizing and planning, the higher the value of the feasibility function, the lower the cost. It means that GA can help find the most economical and efficient solution for the supply chain.

In addition, GA also stands out in its ability to utilize penalty functions. This penalty function is a control mechanism that prevents violations of hard constraints, such as shortages in the order planning process. By applying the concept of penalty functions, GAs can intelligently avoid solutions that violate these "hard constraints" as formulated in Eq. (14).

Table 3. The fitness function generated by a test run of the GA

No	GA parameter				Fitness				
	N	P_c	P_m	G_n	1	2	3	4	5
1	80	0.65	0.02	750	6,166E-05	6,085E-05	6,206E-05	6,25E-05	6,123E-05
2	90	0.75	0.05	750	6,487E-05	6,217E-05	6,026E-05	6,675E-05	6,22E-05
3	100	0.80	0.01	750	6,661E-05	6,458E-05	6,335E-05	6,596E-05	6,958E-05
4	125	0.9	0.03	750	6,431E-05	6,284E-05	6,04E-05	6,854E-05	6,473E-05
5	140	0.85	0.04	750	5,844E-05	6,691E-05	6,208E-05	6,268E-05	5,944E-05
6	150	0.90	0.025	750	6,254E-05	6,501E-05	6,964E-05	6,227E-05	6,103E-05
7	80	0.65	0.02	1000	6,07E-05	6,232E-05	6,151E-05	6,732E-05	5,931E-05
8	90	0.75	0.05	1000	6,018E-05	6,38E-05	6,343E-05	6,26E-05	6,278E-05
9	100	0.80	0.01	1000	6,72E-05	6,64E-05	6,69E-05	6,47E-05	5,78E-05
10	125	0.9	0.03	1000	6,52E-05	6,12E-05	6,81E-05	6,52E-05	6,58E-05
11	140	0.85	0.04	1000	5,894E-05	6,04E-05	6,554E-05	6,341E-05	6,456E-05
12	150	0.90	0.025	1000	6,369E-05	6,39E-05	6,531E-05	6,704E-05	14941725

Note: PoP=Population; P_c=Probability of crossover; P_m= Probability of mutation; G_n=Generation.

Table 4. Total costs generated by a test run of the GA

No	GA parameter				Total costs (IDR)				
	N	P_c	P_m	G_n	1	2	3	4	5
1	80	0.65	0.02	750	16,217,841.67	16,434,250.00	16,113,391.67	16,000,550.00	16,330,733.33
2	90	0.75	0.05	750	15,415,550.00	16,085,066.67	16,595,666.67	14,982,250.00	16,077,650.00
3	100	0.80	0.01	750	15,013,775.00	15,484,816.67	15,784,900.00	15,161,550.00	14,372,708.33
4	125	0.9	0.03	750	15,550,725.00	15,914,566.67	16,556,950.00	14,589,058.33.	15,447,916.67
5	140	0.85	0.04	750	17,111,666.67	14,946,491.67	16,108,758.33	15,953,008.33	16,822,425.00
6	150	0.90	0.025	750	15,988,833.33	15,383,208.33	14,359,333.33	16,057,941.67	16,384,741.67
7	80	0.65	0.02	1000	16,473,433.33	16,046,958.33	16,256,558.33	14,854,425.00	16,861,750.00
8	90	0.75	0.05	1000	16,617,208.33	15,674,100.00	15,764,625.00	15,974,741.67	15,928,233.33
9	100	0.80	0.01	1000	14,881,100.00	15,067,067.00	14,943,392.00	15,466,817.00	17,287,275.00
10	125	0.9	0.03	1000	15,342,483.00	16,332,017.00	14,674,608.00	15,329,783.00	15,204,842.00
11	140	0.85	0.04	1000	16,965,250.00	16,557,133.33	15,257,983.33	15,770,258.33	15,490,508.33
12	150	0.90	0.025	1000	15,699,891.67	15,650,225.00	15,311,800.00	14,917,258.33	14,941,725.00

Note: PoP=Population; P_c=probability of crossover; P_m= Probability of mutation; G_n=Generation.

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This ensures that the resulting solution is not only cost-optimal but also satisfies all relevant planning criteria and constraints. Penalty functions in GA prevent hard constraints, enhance solution robustness, and boost decision-making reliability. Therefore, incorporating penalty functions turns GAs into sophisticated decision-making tools that navigate complex constraints while striving for an optimal solution.

From the experimental results (Table 3 and Table 4), it can be observed that the sixth iteration, which was replicated three times, showed optimal performance in terms of cost. In this iteration, a fitness value of 6.9641E-05 was achieved, which further contributed to calculating the total cost of 14,359,333.33. The details of the search process to achieve this fitness value (Fig. 5), with the achievement occurring in the 744th Generation.

The results of this analysis indicate the potential to improve the search results for a more optimal solution in terms of fitness value, given that the termination of iterations was implemented at the 750th Generation. Although this experiment has designed iteration-stopping endpoints at the 750th and 1000th generations, further consideration is needed to optimize the fitness value achievement through modifications to the termination method. Moving forward, the results of a near or optimal solution of order quantity determination derived by a GA can represent a realistic and complex situation in supply chain management (Fig. 6).

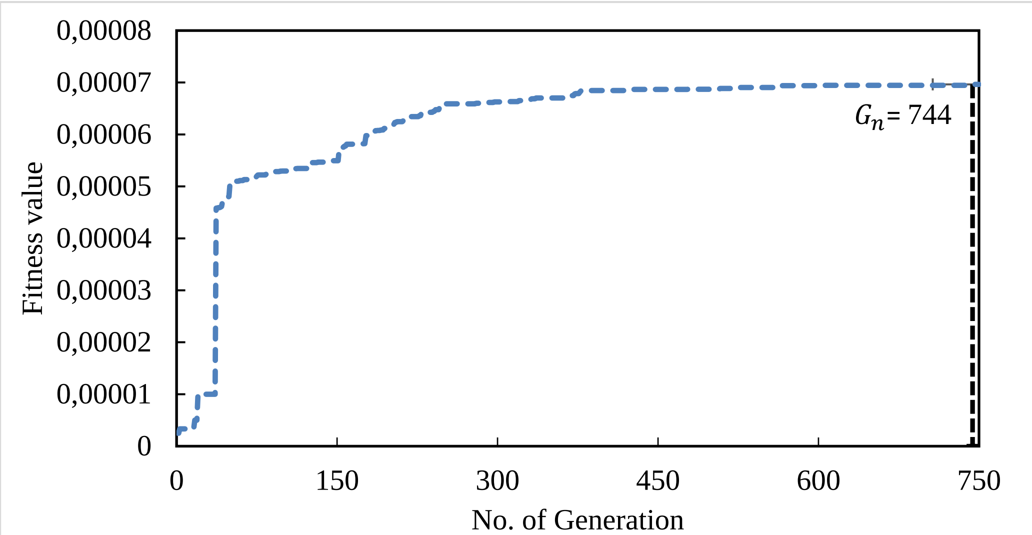


Fig. 5. GA search process in the 6th experiment of the 3rd replication

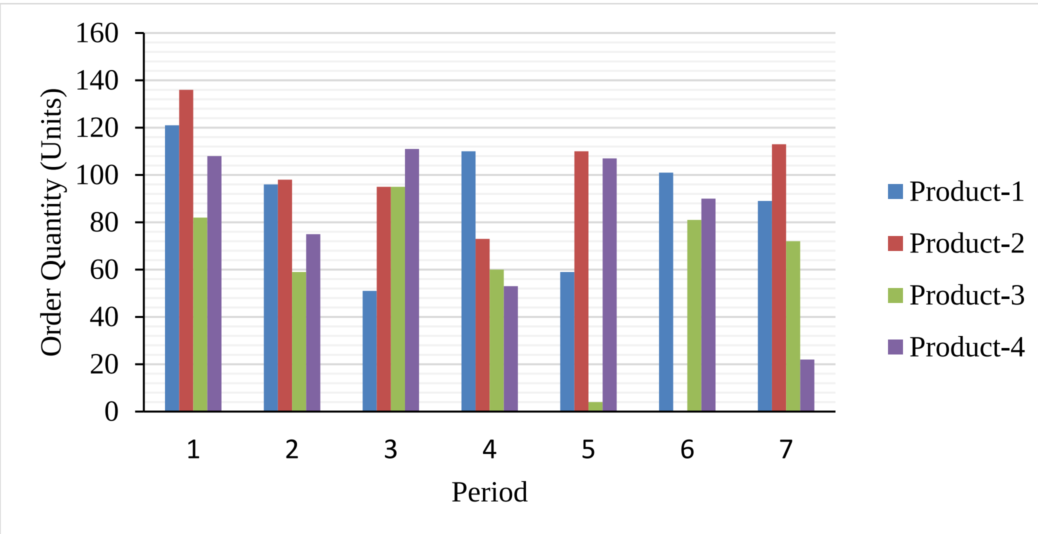


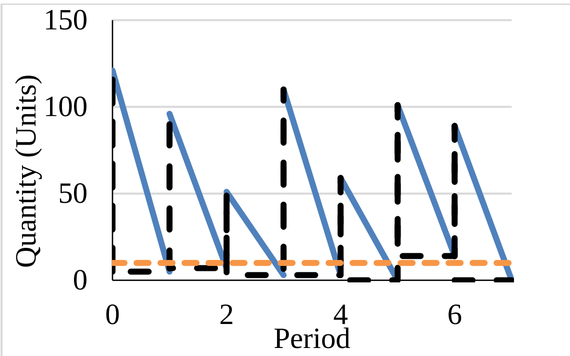
Fig. 6. The near or optimal solution of order quantity generated by GA for each product ordered by distributors to a supplier to meet customer demand

The costs incurred in this scenario result from the decisions made regarding the fluctuating order quantities resulting from dynamic interactions between distributors and suppliers to meet the diverse product requirements of four different customers. The effects of these decisions significantly impact the inventory level at the distributor stage (Fig. 7), with changes in the level of inventory maintained, as well as their influence on the calculation of relevant costs. These complex dynamics comprehensively illustrate how fluctuations in the near-optimal order quantity, resulting from the GA approach, reflect the real dynamics and unique characteristics of the operational environment in a complex distribution system.

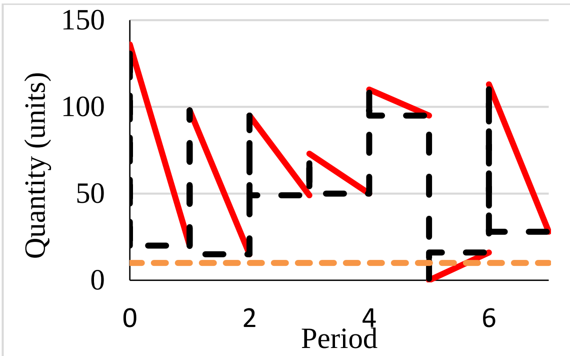
The inventory graph (Fig. 7) depicts a situation where, although the costs incurred reached a minimum, the order quantity solution implemented resulted in an ending inventory that exceeded the maximum capacity. It indicates that although efforts to minimize costs have been successful, increasing inventory capacity needs to be further considered to avoid negative impacts on distribution operations. Increasing inventory capacity to improve operational efficiency can significantly impact perishable products. While increased inventory capacity may reduce the risk of stock-outs and increase product availability, at the same time, products that have a limited shelf life or are sensitive to environmental conditions may experience a higher risk of damage due to the length of storage time.

A deeper analysis of the impact of order quantity decisions on total return and perishable costs (Fig. 8), reveals a fundamental aspect of modern supply chain management. The potential variability in return rates in different periods and the intrinsic characteristics of products that exhibit their susceptibility to changing conditions during the storage process underlies this interpretation.

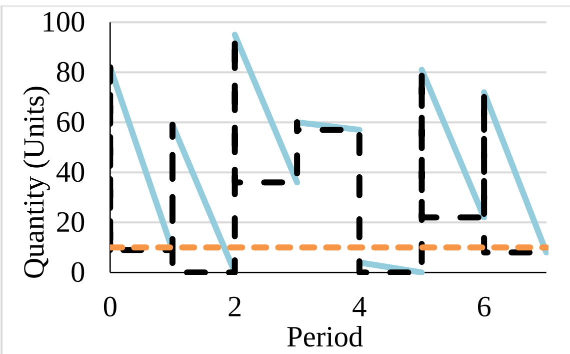
The complex interaction between these factors results in a pattern of cost dynamics that reflects the complexity of the calculations behind the decision-making regarding order quantity. Return rates that reach significant values directly drive the escalation of cost implications, in line with the escalation of the number of returns that occur. Furthermore, the perishable nature of goods exacerbates this cost impact and the increased risk of financial loss caused by potential product damage.



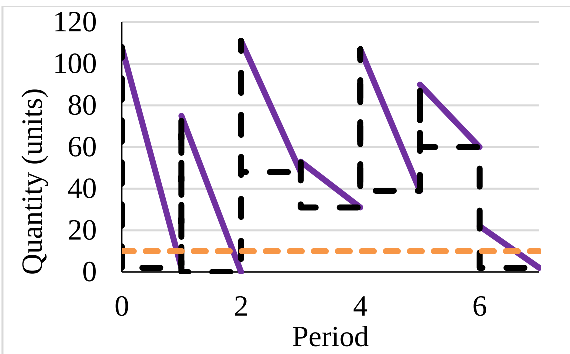
3.1. Product-1



(b) Product-2



(c) Product-3



(d) Product-4

Fig. 7. Inventory charts for each product ordered from distributors to suppliers to fulfil customer demand

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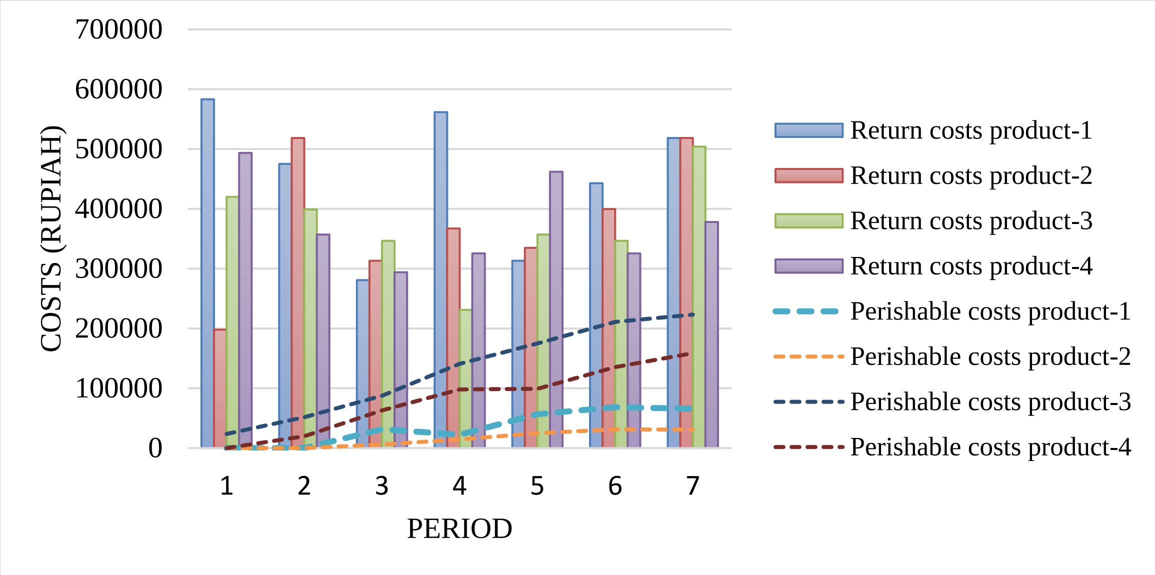

Fig. 8. Total return costs and perishable costs per period per product

In the context of supply chain management that emphasizes cost efficiency, a deep understanding of this dual influence emerges as a central element. Gaining a thorough insight into the correlation between return rate variations and perishability considerations creates a valuable foundation for effective decision-making. Not only does it serve to achieve optimal resource allocation, but it also formulates strategies focused on mitigating costs arising from return activities and management of products that tend to be fragile.

Indeed, combining these comprehensive analyses has far-reaching implications in linking operational decisions with the company's long-term goals, including developing strategies to minimize total costs to support sustainable supply chain efficiency and viability. Therefore, maintaining the right balance between the variability of returns and consideration of perishability is essential in organizing high-quality decision-making

3.2. Managerial and theoretical implications

3.2.1. *Managerial implications*

Managing products with an expiry date, especially bread products, has significant managerial implications for distributors. First of all, distributors need to develop an efficient inventory management strategy. It involves closely monitoring the level of demand for bread products, seasonal patterns, and past sales trends. By deeply understanding customer behaviors and market trends, distributors can better plan orders, avoid excess inventory that can result in wastage, and reduce the risk of stock-outs that can be detrimental to business reputation.

Secondly, close collaboration with suppliers and bread manufacturers is crucial. Distributors need to ensure that the supply chain runs smoothly to avoid delays in product delivery. In this context, good communication with suppliers is important to anticipate obstacles that may arise, such as production or distribution problems. Providing alternative suppliers can also be a wise step to reduce the risk of supply disruptions. In addition, a long-term approach with suppliers in terms of production planning and capacity enhancement can also help overcome any fluctuations in demand that may occur.

Finally, implementing technology and information systems can provide significant benefits in dealing with the challenges of perishable products. Using sophisticated, data-driven inventory management systems allows distributors to track bread inventory projects accurately and respond quickly to changes in demand. Adopting the right technology allows distributors to automate order processes, minimize human errors, and improve overall operational efficiency. In addition, using technology can also help monitor optimal storage conditions to maintain the quality of bread products and extend their shelf life.

Managing perishable products, especially bread products, requires distributors to adopt a strategic approach to inventory management, collaboration with suppliers, and proper

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utilization of technology. By combining these factors, distributors can overcome the challenges arising from the perishable nature of the products and keep the business running smoothly while meeting customer demands well.

3.2.2. *Theoretical implications*

In a theoretical context, the challenge of managing perishable products such as bread products has relevant implications for supply chain management and inventory theory. Firstly, demand and return rate forecasting is becoming increasingly important. Distributors must apply appropriate forecasting methods to accurately predict all bread products' demand and return rates. A forecasting model that integrates sales trends, demand variability, and product deterioration rate will help distributors plan orders more efficiently, reduce the risk of overstock or understock, and improve operational performance.

Secondly, inventory theory also plays an important role in dealing with products with perishable properties. Distributors must consider the trade-off between storage costs and shortage and overstock costs. Inventory models such as lot sizing models extended to include the perishable aspect will help determine the optimal size of orders and appropriate ordering intervals. Using these concepts can help reduce excess inventory, increase product availability, and optimize production and delivery times to maintain product freshness in the context of perishable bread products.

Overall, perishable products such as bread provide valuable theoretical contributions to developing inventory theory and coordination concepts in supply chain management. Distributors must apply and combine these concepts judiciously to face the challenges arising from the product's perishable nature and maintain a balance between operational efficiency and customer satisfaction

3.2.3. *Integration with previous research*

The proposed lot sizing models show a significant shift compared to previous models. One of the main differences lies in the approach to demand dynamics. Current models consider dynamic demand, accommodating more realistic fluctuations in customer demand. The study by Li *et al*. [38] suggested that modelling dynamic demand can lead to more accurate results in stock planning. On the other hand, previous models often rely on assumptions of fixed or very slowly changing demand [39].

When comparing current lot sizing models with classical models such as Economic Order Quantity (EOQ), another difference arises in the complexity of the calculations. EOQ models are generally based on simple assumptions, such as fixed ordering, storage costs, and constant demand [40]. However, research by Singh and Pattanayak [39] showed that the EOQ model can be extended by considering dynamic demand and evolving storage costs. Alternatively, the current model applies a more comprehensive approach by considering more complicated demand dynamics, total ordering, and inventory costs that can evolve. Research by He *et al*. [40] showed that considering additional factors such as perishable rate can improve stock planning for products prone to spoilage.

While there are significant differences between the current and previous models, there are important points of similarity. Both models remain focused on the main objective of stock planning, which is to ensure the availability of the right stock at the right time. In this regard, both consider careful order planning to avoid the risk of under-stocking or over-stocking. Thus, even though the current model has more sophisticated components, such as more complex demand dynamics and perishable rates, the core of stock planning remains focused on efficient and effective inventory management.

It is also important to note that since the current stock planning model involves complicated and complex calculations, meta-heuristic methods such as GAs are used to search for the near or optimal solution in determining the order quantity. This technique illustrates a higher level of complexity in the current stock planning process, which may be necessary to deal with greater complexity in a constantly changing business environment.

4. CONCLUSION

This research is based on an empirical investigation of perishable products, emphasizing order planning for bread products. Beyond the challenge of demand uncertainty, this research investigates the complexities of managing perishable products. These complexities include varying shelf-life ranges across products, uncertain return rates, considerations spanning multiple periods, dynamic fluctuations in demand,

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and the complexity required in organizing inventory from the manufacturer to the distributor and ultimately to the end retailer. This research presents an innovative methodology that focuses on lot size optimization, especially on the unique characteristics of perishable products, thus contributing substantially to the evolution of inventory direction in highly complicated industrial environments. In addition, this research dedicates substantial attention to pragmatic and consequential issues, especially those covering the inherent volatility of return rates and deterioration rates at the time of storage, which present challenges to manufacturers and distributors. Remarkably, this particular aspect of real-world systems has not been thoroughly investigated until now, making it an important step toward developing interesting applications.

This research aims to reduce the total ordering cost by optimizing the order quantity for perishable products, which includes multi-product and multi-period considerations. Due to the complexity of the problem, GA is proposed by experimenting with the combination of several parameters, namely crossover, mutation, population, and Generation. These experiments were conducted to maximize the minimal planning cost's feasibility value. The optimal or near-optimal order quantity generated by GA greatly affects the total cost, but the solution is difficult to know the pattern due to the dynamic nature of demand. In addition, the determination of the order quantity is affected by the return and damage rates. However, experiments using GA have successfully achieved the intended value to solve the perishable product problem. This study contributes to helping distributors effectively minimize wastage arising from expired or perishable products while simultaneously meeting customer demand more efficiently. For future research, applying inventory models with discounts (e.g. lot sizing models with discounts related to order quantities) can also be a relevant alternative in the face of demand fluctuations associated with bread products. It aims to determine the effect of discounts on sales acceleration in avoiding the occurrence of return products. In addition, some metaheuristic methods, such as ant colony optimization, simulated annealing, and particle swarm optimization, can be used to compare with the current results regarding performance and computation time. Then, larger problem scale can be explored for future works.

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